

Satellite imagery and deep learning framework for highway construction with minimal vegetation impact

Meenakshi, Rajesh Thalwagal Matha

Department of Computer Science and Engineering, Dayananda Sagar University, Bengaluru, India

Article Info

Article history:

Received Feb 25, 2025

Revised Jul 13, 2026

Accepted Jul 21, 2026

Keywords:

Artificial intelligence
Computer vision
Convolutional neural network
Deep learning
Normalized difference
vegetation index
Satellite image

ABSTRACT

Constructing roads through vegetated terrain forces a trade-off between minimizing ecological harm and preserving constructional ease. This work presents a unified, end-to-end framework that reconciles both objectives, with three major contributions. First, propose a hybrid perception model that fuses a graph convolutional network (GCN)—capturing scene-level spatial context—with a capsule network (CapsNet) that encodes part-whole relationships for reliable detection of small, clustered vegetation; this configuration attains an average precision (AP) of 0.925, average recall (AR) of 0.948 (intersection over union (IoU) = 0.5), and 98% land-cover classification accuracy on unseen data. Second, we introduce an ecological-sensitivity cost map fusing vegetation normalized difference vegetation index (NDVI) with terrain slope, over which we evaluate Dijkstra, A*, a novel Eco-Aware A* embedding a vegetation-avoidance penalty, and a non-dominated sorting genetic algorithm II (NSGA-II) multi-objective search that jointly minimizes path length and vegetation damage. Third, on a benchmark modeled on the Bengaluru–Kanakapura road (NDVI = 0.7, slope = 0.3), the eco-sensitive route lowers segment NDVI by roughly 69% and eliminates all high-canopy exposure while adding only about 8% to path length versus an optimized non-vegetated route. Together, these components enable automated, ecologically aware road planning directly from imagery.

This is an open access article under the [CC BY-SA](#) license.



Corresponding Author:

Meenakshi

Department of Computer Science and Engineering, Dayananda Sagar University
Bengaluru, India

Email: meenakshib437@gmail.com

1. INTRODUCTION

Artificial intelligence (AI) has become a transformative force in infrastructure condition monitoring, reshaping modern asset management practices against the backdrop of fast-paced urbanization and the push for sustainable development. Conventional approaches to this problem have long relied on manual inspection, ground-based sensors, and periodic visual surveys to gauge the state of roads, bridges, buildings, and similar assets [1]–[4]. These methods work up to a point, but they carry real limitations: they demand substantial labor, consume significant time, cover only limited areas, and cannot sustain continuous oversight of extensive infrastructure networks. Compounding these shortcomings, traditional monitoring largely ignores the environmental side of infrastructure development, leaving vegetation loss and broader land-cover change in surrounding areas unaccounted. Some of the ways in which the environment could be affected negatively along the routes may not be well considered in road alignment.

The shortage of infrastructure in the country makes transport routes crucial for the nation's development. Remotely sensed data and machine learning (ML) algorithms have increased the accuracy of land-cover classification, whereas multi-objective optimization makes it feasible to navigate trade-offs

among multiple objectives. Yet, chain planning still entails disconnected stages: perception (classification/segmentation) is designed independently from routing, or optimization is conducted over a crude, heuristic cost grid. EcoRoute I-Net remedies the lack through the following integrated and modular system ranging from perception to decision: a base model augmenting segmentation/classification pipeline (ViT-Large + Swin Transformer), yielding high-resolution thematic maps. Empirically, the integrated system is accurate and yields constructive savings relevant to the abstracted project requirement. Contributions: a unified perception-to-decision framework integrating foundation model-based land cover mapping with multi-objective routing. A mathematically based composite cost surface for vegetation, hydrology, terrain, and constructability terms.

In recent years, AI-based approaches, particularly those that make use of satellite imagery, have emerged as powerful and scalable tools for infrastructure monitoring and management. High-resolution satellite images make it possible to observe large geographic areas and collect updated information at frequent intervals, enabling near real-time monitoring of critical infrastructure assets [5]–[8]. By shifting from manual inspection to AI-driven satellite image analysis, infrastructure health can be efficiently assessed across large networks while the same models simultaneously detect and quantify vegetation loss from expansion, maintenance, and urban development, jointly supporting sustainable, resilient development [9]–[11]. Substantial obstacles still stand in the way: the sheer scale of available data, the subtlety of many structural defects, and the difficulty of telling authentic vegetation loss apart from changes driven by season or climate. These factors keep the fusion of high-resolution satellite data with AI-based monitoring an active research frontier, one that calls for deep learning models capable of picking up on fine-grained cues tied to structural wear, erosion, and shifting vegetation cover. This project responds with a unified, real-time framework built on convolutional neural networks (CNNs) that flags degradation signals such as cracks, wear, and erosion while simultaneously measuring nearby vegetation loss [12]–[14], giving planners a scalable, cost-effective, automated substitute for manual inspection. In practice, this enables proactive maintenance, cuts operating costs, and limits harm to vegetation [15], [16], in keeping with smart city objectives and wider sustainability targets.

The paper makes three contributions. First, it presents a single perception-to-decision framework that joins foundation-style land-cover mapping with multi-objective routing. Second, it defines a composite cost surface, in closed mathematical form, that combines vegetation, terrain, and constructability terms. Third, it introduces an Eco-Aware A* planner and a non-dominated sorting genetic algorithm II (NSGA-II) Pareto search that make the vegetation-versus-feasibility trade-off explicit, and it releases a fully reproducible implementation.

2. LITERATURE REVIEW

Monitoring infrastructure development and vegetation cover dynamics has become a very important process with regards to modern urbanization, climate trends, and an increase in ecosystem degradation. The combination of satellite imagery and AI, especially with regards to deep learning, has significantly enhanced the process of observing structural development and vegetation destruction on a large spatial and temporal scale. The initial process was mainly dominated by observations and rule-based systems, whereas modern systems are increasingly upgrading to deep learning and multi-temporal satellite images.

Early accomplishments proved the capability of fine-scale vegetation analysis. The progress achieved by Arkin *et al.* [1] paved the way for the analysis of vegetation loss based on very high-resolution imagery. This work focused on the assessment of the severity of fires using airborne imagery. Fine-scale vegetation analysis proved workable in several early studies. Working from very-high-resolution airborne imagery, Arkin *et al.* [1] assessed fire severity and, in doing so, advanced the measurement of vegetation loss. Bai *et al.* [2] proposed an improved luminance-contrast saliency map built on interferometric synthetic aperture radar (InSAR) coherence differences and used it to delineate burned areas. Plomer *et al.* [3] took a CNN-based route, combining radar and optical imagery to map burned areas and capture fire-driven vegetation loss.

Bulatov *et al.* [4], [5] moved past two-dimensional imagery altogether, using three-dimensional point clouds to separate vegetation from built structures and again recovering vegetation loss reliably. Saliency map techniques were further introduced in the analysis by [2] using the InSAR coherence difference in determining the burned areas. This process indicated the effectiveness of the analysis techniques used in the study. Techniques based on the use of CNN were further explored by [3]. The work focused on the analysis based on the usage of radar and optical imagery in the burn area determination. This indicated the effectiveness of the analysis in capturing loss due to vegetation fires. In addition to the analysis techniques based on two-dimensional imagery, techniques based on three-dimensional point clouds focused on the

analysis between vegetation and man-made structures were further explored by [4]. The process indicated the effectiveness in capturing the loss due to vegetation in the selected region.

Improvements in deep learning techniques combined with the advent of high-resolution satellite data have further increased the accuracy of vegetation loss detection. Cho *et al.* [6] used deep learning techniques in combination with PlanetScope satellite imagery for burned area identification, increasing the accuracy of unitemporal vegetation loss detection. Dixon *et al.* [8] presented the concept of spatiotemporal deep learning techniques for recognizing canopy-scale tree death in response to forest fires for precise vegetation loss monitoring over time. Javed *et al.* [9] presented a deep learning-based method for change detection of urban forest cover using very high resolution (VHR) satellite imagery. As deep learning matured and higher-resolution data became available, vegetation-loss detection improved again. In studies [6], [7] applied deep learning to unitemporal PlanetScope imagery for burned-area identification and reported higher accuracy.

Dixon *et al.* [8] developed spatiotemporal techniques that recognize canopy-scale tree mortality after fire, which lets the process be followed precisely through time, while Javed *et al.* [9] detected change in urban forest cover from VHR imagery. Vegetation recovery after disturbance drew attention too. Priya and Vani [10] built an unsupervised deep model for post-fire vegetation change and recovery; Sur *et al.* [11] tracked vegetation degradation across India from multi-sensor imagery; and Anand *et al.* [12] linked landscape change to land-surface temperature and vegetation indices. Regional studies have paid particular attention to climate-driven vegetation change. Shukla *et al.* [13] carried out a spatio-temporal analysis of vegetation cover from linear imaging self-scanning sensor (LISS)-IV imagery with AI/ML change detection. Other work applied CNNs to PlanetScope data for accurate land-use and land-cover classification. Deep-learning remote sensing has also been used to flag normalized difference vegetation index (NDVI)-related degradation in mining and habitat zones and to estimate fractional vegetation cover from Sentinel-2 time series, and hybrid recurrent neural network (RNN)-CNN models have been put forward to forecast NDVI for long-term vegetation-health studies [13]–[16].

Review articles have since drawn these threads together, pointing to a clear move toward fusing heterogeneous data sources and to the growing dominance of deep learning in biodiversity monitoring and deforestation mapping [10], [17]. Recent studies have widely employed deep learning and remote sensing for vegetation monitoring, change detection, and environmental assessment using multi-sensor satellite imagery. Regional research has utilized CNNs, NDVI, Sentinel-2, PlanetScope, and hybrid RNN-CNN models to map vegetation dynamics, climate-induced changes, and long-term vegetation health. Comprehensive reviews emphasize multimodal data fusion, biodiversity monitoring, semantic segmentation, and large-scale deforestation detection. Infrastructure-related studies have contributed through land-cover segmentation, highway path optimization incorporating land-use dynamics, the A* algorithm for optimal routing, and Huete's SAVI for improved vegetation detection. Building on these advances, Priya and Vani [10] achieved over 96% accuracy in distinguishing genuine vegetation loss from spurious changes, demonstrating the potential of deep learning for eco-sensitive infrastructure planning.

Matyukira and Mhangara [17], in a scientometric review of the literature, found that neural networks dominate the domain and that CNNs in particular have become standard because of their ability to learn hierarchical features directly from raw input data. This motivates the use of CNN and graph convolutional networks (GCN) based approaches in this project. Liu *et al.* [18] offer a survey of road extraction techniques based on deep learning that include fully supervised, semi-supervised and unsupervised approaches and identify relevant datasets and benchmarks for the road segmentation module developed here. Krejcar and Namazi [19] explores the role of AI in remote sensing more generally, including land cover classification, object detection, and disaster response, but also identifies challenges that the combined GCN-capsule network (CapsNet) approach presented here aims to address, specifically related to generalizability, fusing of multi-source data, and computational efficiency. Taken together, this body of literature includes vegetation loss detection, vegetation classification and mapping methods, road extraction methods, and more broadly AI approaches for remote sensing.

Ienco *et al.* [20] propose time-series waveform and imagery network for satellite-fusion (TWINS), a dual branch deep learning system which combines Sentinel-1 radar and Sentinel-2 optical time-series data through a convolutional gated recurrent unit (ConvGRU) architecture coupled with attention mechanisms in order to take advantage of complementary strengths of the data in space and time. It demonstrates that this approach can enhance land-cover classification accuracy [21]. Continental-scale vegetation pattern modelling is well explored through multimodal earth observation foundational models [22]. Vision-based graph neural networks for earth observation have demonstrated advantages in land cover classification. Feature pyramid networks and fully convolutional architectures have been demonstrated to provide robust and accurate per-pixel change detection in remote sensing. Efficient and robust tree based models like LightGBM serve as strong baselines for large-scale classification tasks [23]–[24]. Zoph *et al.* [25] introduced neural architecture search network (NASNet), using neural architecture search to automatically discover a transferable

convolutional "cell" on a small proxy dataset (CIFAR-10) that could be stacked to scale up to large-scale image recognition. Their searched architectures surpassed hand-designed networks on ImageNet while lowering computational cost, demonstrating that learned architectures can transfer effectively across datasets and tasks.

The above discussion on the state of the art demonstrates a clear area where significant advancement can be made: there is a dearth of frameworks that jointly address infrastructure change and associated vegetation loss using a single, integrated pipeline. Utilizing multimodal satellite imagery in combination with deep learning methods provides a promising avenue to construct such holistic solutions. More broadly, the convergence of ML, geospatial analysis, and optimization in infrastructure development has become an active research direction, one that this project's segmentation, cost mapping, and road-planning optimization builds upon. Satellite-based land classification has advanced considerably through deep learning, with fully convolutional networks setting an early benchmark for semantic segmentation and U-Net Ronneberger *et al.*, [26], first designed for biomedical images, later repurposed to classify land cover into forests, roads, water bodies, and plains. Cost mapping, which assigns each land category a value reflecting its ecological sensitivity and construction difficulty, extends earlier geographic information system (GIS)-based approaches that argued for embedding ecological factors directly into infrastructure planning, with newer studies pairing GIS and ML to generate cost maps that adapt dynamically to changing conditions. Long-standing algorithms such as Dijkstra [27] and A* Hart *et al.*, [28] continue to anchor shortest-path computation and have been adapted to cost-weighted geospatial settings, with recent research coupling them to machine-learning-derived cost maps so that computed routes minimize financial and environmental cost together.

Advances in high-resolution imagery and data processing now support fine-grained terrain analysis, and an increasing body of work fuses remote sensing with ML to locate construction paths with the least ecological disruption. Sustainability considerations have likewise moved to the center of infrastructure planning, with prior studies documenting the environmental toll of road building and calling for methods that limit habitat fragmentation and deforestation, shaping frameworks that weigh economic gains against ecological costs. Translating analytical output into actionable guidance depends on effective geospatial visualization, and progress in GIS and ML has made interactive, interpretable visual tools available to stakeholders. Beyond roads, comparable segmentation and optimization techniques have found use in urban planning, disaster response, resource allocation, and utility network design, pointing to the broader applicability of this methodology. Tracking how infrastructure grows and how vegetation cover shifts has taken on new importance amid modern urbanization, a changing climate, and the steady loss of ecosystems. Pairing satellite imagery with AI, and with deep learning in particular, has made it far easier to observe both construction activity and vegetation loss over large areas and long periods. The earliest studies leaned on manual observation and rule-based systems; current pipelines increasingly rely on deep learning applied to multi-temporal imagery.

3. METHOD

Data acquisition: in this study, the satellite imagery used was provided by several renowned space agencies, such as the Indian Space Research Organization (ISRO), NASA, the European Space Agency (ESA), and the space studies institute in California which hosts satellite data across various resolutions in spatial, spectral, and temporal characteristics. Considering the fact that our area of interest is This study prioritizes satellite data that can be used to study various terrain and climate conditions in India; therefore, this study selected images from ISRO's LISS-III to develop and test our model. LISS-III has 4 spectral bands—both visible and the near-infrared bands possess a spatial resolution of 23.5 m over a swath width of approximately 141 km whereas the shorter wavelength infrared band possesses a coarse spatial resolution of 70.5 m and swath width of approximately 148 km. The sensor provides decent temporal coverage with its revisit time of 24 days, freely available through Bhuvan, the national geo-portal, over a span of more than a decade comprising historical and multi-seasonal imagery with relatively less cloud cover. Imagery was collected from several established agencies, among them the ISRO, NASA, ESA, and the space studies institute, whose archives differ in spatial, spectral, and temporal resolution. Since the study focuses on Indian regions, this study favored imagery matched to Indian terrain and climate and settled on ISRO's LISS-III instrument for building and testing the model. LISS-III records four spectral bands. The two visible bands and the near-infrared band give 23.5 m resolution over a swath near 141 km, and the short-wave infrared band works at 70.5 m over a swath of about 148 km. Its 24-day revisit cycle keeps temporal coverage steady, and because the data are free through Bhuvan, India's national geo-portal, more than a decade of multi-seasonal, mostly low-cloud scenes is available, which makes the sensor well suited to training robust segmentation models.

This study also draws on the public SpaceNet dataset, which offers high-resolution imagery of urban and semi-urban areas together with detailed ground-truth labels for buildings, roads, and other structures.

Those labels make supervised training and reliable evaluation possible. Since SpaceNet is widely utilized in GIS applications, urban planning, and disaster response, it provides a relevant benchmark for evaluating model accuracy in segmenting various urban features under varying conditions. The work additionally makes use of the publicly available SpaceNet dataset that sourced on Kaggle. The SpaceNet dataset contains ultra-high-resolution pictures of cityscapes/suburban and includes corresponding land-ground truths of buildings, streets and others; these data allow to make a proper training of any supervised learning model as well as an unbiased evaluation of the model. The results have been quantitatively analyzed in terms of intersection over union (IoU), the most common and accepted metric for quantifying segmentation performance. IoU is defined as the ratio of overlap to union area. With 'A' and 'B' the set of pixels corresponding to ground-truth and estimated segmentation maps, respectively and $A \cap B$ the intersection, IoU is calculated as in (1).

$$IoU(A, B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|} \quad (1)$$

IoU also known as the Jaccard Index, measures the similarity between the predicted region (A) and the ground-truth region (B) by dividing their overlapping area by their combined area. An IoU value closer to 1 indicates higher segmentation accuracy, while 0 indicates no overlap. The research framework describes a workflow that uses a pair of images from the same geographic location taken at different times (for example, satellite or aerial images), as shown in Figure 1. First, the input images are preprocessed through: resize to a uniform scale, normalization, extraction of 256×256 patches, encode annotation, data augmentation (rotation, flipping, and zooming). Next, the pairs of preprocessed images are feed into the U-Net network for feature extraction and change detection, output feature maps that highlight the affected areas.

Architectural flowchart and process diagram of the framework respectively: first use image to input, second to preprocess images, third use deep learning to detect whether it is vegetation, if not then detect if vegetation loss, and then to decide how to minimize vegetation loss as shown in the Figures 1 to 3. The proposed framework follows a systematically procedure for feature extraction, classification, and deployment using CapsNets and GCN as shown in the Figure 2. The procedure starts with data collection from available sources, followed by preprocessing of the data that includes cleaning, normalization, denoising, and enhancement to increase the data quality, finally splitting the data into training, validation, and test sets. The preprocessed data is first passed through CapsNet where local, spatial features are extracted and encoded in a hierarchical representation, which preserve the relationships between objects.

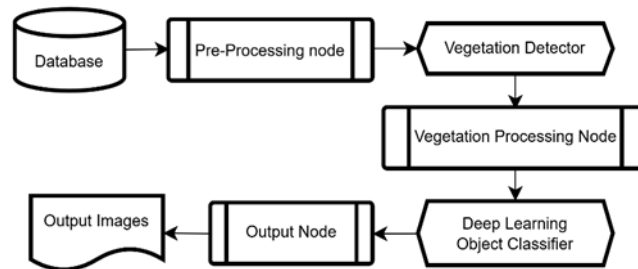


Figure 1. Proposed work framework

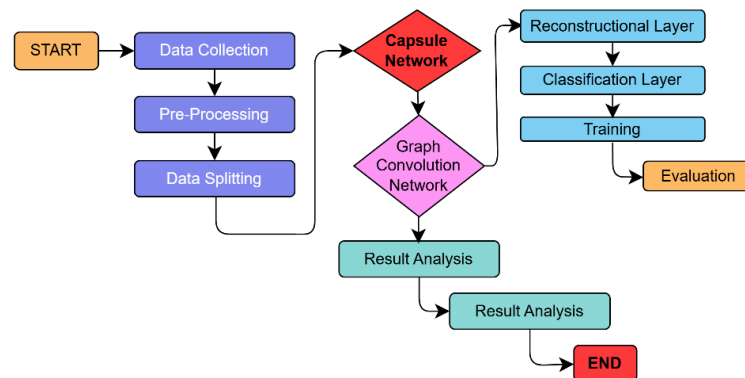


Figure 2. Architectural flowchart and methodology diagram

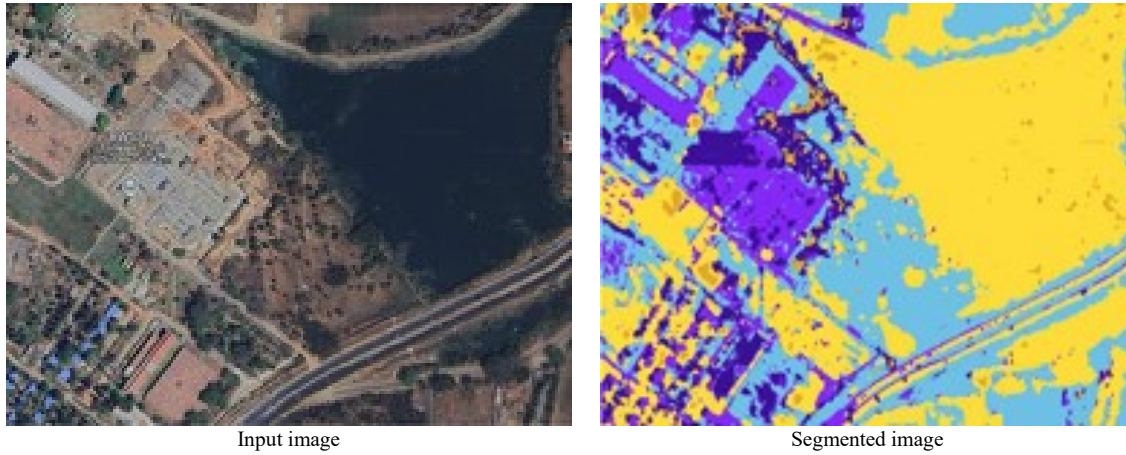


Figure 3. Sample input image used for training and segmented image

These high-level feature vectors then feed into a GCN, which learns complex dependencies and relations within and between data samples. A reconstruction layer then maps the GCN features back to the lower-level features, preserving key information from the capsules and acts as a regularization term. These reconstructed features are input into a classification layer to generate the output predictions, i.e., class labels. Model parameters are optimized by training and utilizing the backpropagation algorithm and an appropriate optimizer to minimize classification error, then evaluate the trained model using accuracy, precision, recall, F1-score, and analyze the results. Compare its performance with other methods to test if there is significant improvement in performance and compare against them. After valid, model is ready for deployment that can be utilized to real world problems of different areas like, remote sensing, intelligent transportation, and cybersecurity. This study designs a framework based on CapsNet and GCN which takes advantage of feature extraction and learning spatial correlations and global relationships. Segmentation accuracy is defined based on the overlap of the predicted regions and the ground truth regions. The prediction is considered correct if the IoU is at least 0.5, i.e., the predicted mask and the ground truth region have at least 50% intersection over the union. Precision $\text{IoU} \geq 0.5$ is defined as in (2).

$$\text{Precision}_{\text{IoU} \geq 0.5} = \frac{TP_{\text{IoU} \geq 0.5}}{TP_{\text{IoU} \geq 0.5} + FP_{\text{IoU} \geq 0.5}} \quad (2)$$

Where in (2) denotes the precision calculated at an IoU threshold of 0.5 or greater. Here, $TP_{\text{IoU} \geq 0.5}$ represents the true positive detections that achieve an $\text{IoU} \geq 0.5$, while $FP_{\text{IoU} \geq 0.5}$ denotes the corresponding false positive detections at the same threshold. Recall: $\text{IoU} \geq 0.5$; recall measures the ability of the model to correctly identify all relevant instances and is defined as in (3).

$$\text{Recall}_{\text{IoU} \geq 0.5} = \frac{TP_{\text{IoU} \geq 0.5}}{TP_{\text{IoU} \geq 0.5} + FN_{\text{IoU} \geq 0.5}} \quad (3)$$

Where in (3) means false negatives related to TP regions with IoU values under 0.5. To measure model performance, this study uses two aggregate scores: when summed over all ground truth objects and a IoU of 0.5 they define two summary measures (average precision (AP) at IoU 0.5 and average recall (AR) at IoU 0.5) that can be combined with per region metrics and overall IoU. These represent an unambiguous way to judge performance of an instance segmentation method for satellite images. Using this standard as inspiration this study develop a two-stage instance segmentation pipeline. A graph convolutional neural network (GCNN), first encodes node and edge features derived from the grid that represents the image, providing a representation of global spatial dependencies and long-range structural patterns across the entire image [29]. A CapsNet, CNN (capsule) processes this representation and refines it into segmentations by modelling relationships of parts of the segmentation being within segmentation for example. A full end to end system trained on raw images with accompanying metadata, the network outputs one segmentation mask per instance. This study discovered in early experiments that tiny buildings, often appearing clustered, are hard to distinguish from one another and their impact on performance is hidden within AP and AR measures, which give equal weight to every object irrespective of physical scale.

This study combat this through designing our loss function with two complementary weighting schemes, the first up weights pixels near other segments thus strengthening the borders of adjacent objects, while the second increases the weights of small segments so they are not underrepresented as they contain a relatively small proportion of the overall pixels. It is composed of two loss components: a cross-entropy loss term penalizing classification accuracy and a Dice loss term which penalizes incorrect spatial localization and weak localization, this study found that training with a combination out performed each component on its own. Image patches were padded (reflectively) to size 320×320 this ensured that the whole object was preserved when segments were tiled along borders and it is an effective way to stop objects from being cropped.

Ground truth masks were generated from polygon-based annotations so that we can provide pixel-based predictions for comparison with the loss function which can also act on pixels directly, it also ensured that we had the same type of input for the loss function and our network's predictions. A variety of common image augmentations were applied during training, which helps the network to generalize. These were horizontal and vertical flipping, random rotations of up to 4 around every 90, a small variation in contrast, and a small variation in brightness. The network was trained with the 1-cycle learning rate schedule to help speed up convergence and improve generalization of the final network [30].

Table 1 shows 0.925 of AP and 0.948 of AR at IoU = 0.5 thresholds for held out test set demonstrate model's capacity for this complicated satellite images segmentation application. Through that, infrastructure can be evaluated considering their effects on vegetation cover reduction due to expansion of infrastructure, growth of urban area, and land cover changes. Inspired by efficient training techniques demonstrated at Stanford's DAWNBench competition—a contest designed to reward rapid, low-cost training on benchmarks such as ImageNet and CIFAR-10—we adopted the 1-cycle learning rate policy developed in earlier work and implemented using the fast AI library. The policy cycles the learning rate throughout a single training run. This approach allows training to rapidly explore the loss landscape efficiently while avoiding the shallow, non-generalizing sharp minima. The Stochastic gradient descent (SGD) method with momentum—which, according to this study, has proven to be robust and capable of producing models with better generalization ability—was used with a batch size of 32. Training was performed in several phases: Initially, a brief warm-up phase trained only the non-pretrained decoder layers for one epoch with a learning rate of 6.

This allowed the randomly initialized decoder layers to stabilize without disrupting the learned feature maps of the pretrained encoder. After this, the entire network was unfrozen and trained for 20 epochs according to the 1-cycle policy: learning rates increased linearly from 0.15 to 6 over the first 45% of the run to allow broad exploration and escape local minima; rates decreased linearly back to 0.15 by the 90% point to settle into a stable basin; and finally, rates were reduced linearly to 0.0015 over the final 10% for fine convergence. Momentum was adjusted inversely to learning rate during all 1-cycle training phases, so as not to overshoot the loss at higher learning rates but still maintain some downward motion at low ones. Following the full 20 epoch 1-cycle training, this study performed two additional cycles of fine-tuning with learning rates oscillating between 0.05 and 1 before ending with a learning rate of 0.05 in the final cycle to refine the model without risking catastrophic forgetting.

Table 1. Training matrix for the dataset

	Number of epochs	Time for training	Accuracy	Precision	Recall
Cycle 1	10	84 ms/step	97.23	95.01	96.14
Cycle 1 with cylindrical learning rate X2	50	94 ms/step	98.34	96.45	97.56

Overall, a combination of this multi-phase strategy—warm-up, full 1-cycle, and cyclical fine-tuning yielded rapid convergence while ensuring robust generalization. The model was trained for both 6-label and 3-label variations of the semantic segmentation of aerial imagery dataset using example images, with the latter producing a more coarsely grained output classification. Route optimization algorithms: on this surface, the cost of stepping from cell u to an 8-connected neighbor v is the average traversal cost of the two cells, scaled by the Euclidean step length $d(u, v)$, which is 1 for orthogonal moves and $\sqrt{2}$ for diagonal ones as in (4).

$$w(u, v) = \frac{1}{2} (C[u] + C[v]) \cdot d(u, v) \quad (4)$$

Edge weight function given in (4), which explain about the traversal cost of an edge joining nodes u and v is taken as the mean of the endpoint costs, scaled by the geometric distance between them: where, $w(u, v)$ is weight (traversal cost) assigned to the edge between nodes u and v , $C[u]$, $C[v]$ is ecological/vegetation cost value at nodes u and v respectively, $d(u, v)$ is Euclidean (or geodesic) distance between nodes u and v in metres. The factor $\frac{1}{2}$ averages the endpoint costs, so that an edge crossing from a

low-cost cell into a high-cost cell is penalized proportionally to the mean impact along its span, while the multiplication by $d(u, v)$ makes the weight extensive in path length. This study compares four planners. Dijkstra runs a uniform-cost search and returns a provably optimal least-cost path, but it expands nodes in every direction [25]. A* adds an admissible Euclidean heuristic $h(a, b) = c_{min} \|a - b\|$, with c_{min} the smallest cell cost; this steers the search toward the target and cuts the number of expansions while keeping the path optimal on the composite surface.

Proposed Eco-Aware A*. The proposed planner adds an explicit vegetation-avoidance term to the edge model, controlled by a weight λ , so the search leans toward low-canopy corridors as in (5).

$$w(u, v) = \frac{1}{2}(C[u] + C[v]) \cdot d(u, v) + \lambda \cdot V[v] \cdot d(u, v) \quad (5)$$

Eco-Aware edge weight (5), explain the heuristic stays admissible with respect to the base cost, so the search remains efficient, and the extra term pulls the route away from dense vegetation. This study set $\lambda = 0.9$ in the experiments. Since one fixed weight cannot express every planner's priority, also provide an NSGA-II multi-objective search. Candidate corridors produced across a range of eco-weights are evolved with fast non-dominated sorting and elitist selection, minimizing two objectives at once, cumulative length-cost and cumulative vegetation exposure, and the search returns a Pareto front. A knee-point rule then picks the solution nearest the ideal point for reporting.

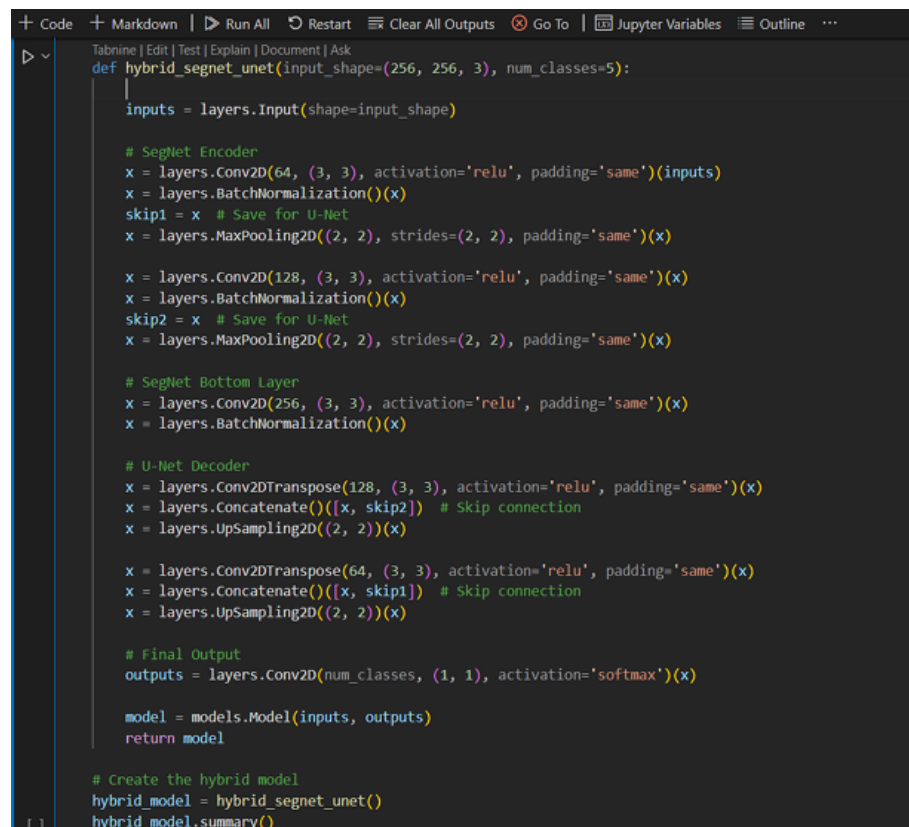
The route-optimization pipeline is self-contained and reproducible. So that the whole method can run without downloading large imagery tiles, it generates a physically plausible benchmark scene deterministically: a smooth elevation field with a high-slope ridge, a dense forest belt lying across the direct line between the endpoints, and an impassable riparian barrier. This setup puts the vegetation versus feasibility trade-off in plain view and lets all planners be compared on identical inputs. Sample satellite images used for training the proposed model along with their corresponding segmented outputs as shown in Figure 3. The segmented images illustrate the successful extraction of vegetation and other land-cover regions, demonstrating the effectiveness of the proposed segmentation approach in accurately identifying terrain features.

4. RESULTS AND DISCUSSION

Incrementally increasing the number of GCN layers and blocks within CapsNet module can systematically reduce model misclassifications of smaller objects and further separate densely arranged instances. Subsequently, further fine-tuning to specialize in segmenting accurate instance boundaries and better separating closely-packed small objects was conducted and the vegetation-detection code is shown in the Figure 4. The semantic subdivision code as shown in Figure 5 and results of the proposed work as shown in Figure 6. When this study train on the 3 labels dataset, the same model produced a slightly lower performance metric, due to class imbalance. In contrast, the model trained on the Label datasets achieved an accuracy score 85%. The proposed GCN-CapsNet model was trained using the satellite imagery dataset following the procedure described in methodology section. To identify the most effective model configuration, this study systematically experimented with several parameters during training and evaluation. In particular, this study varied the segmentation confidence threshold (θ) from 0.3 to 0.8 in order to determine the setting that yielded the best instance-level segmentation performance. In addition to threshold tuning, multiple architectural configurations were explored by changing the depth of the network. Various configurations of the GCN and capsule blocks were compared and contrasted to determine their effects on segmentation accuracy. The overall pixel-wise accuracy did not change substantially-primarily since the proportion of background pixels was far greater-but even a few misplaced foreground pixels proved to have a strong impact on the overall values for precision and recall. Finally, evaluation was performed on the official test set and a number of different key performance metrics, namely AP and AR were measured.

Table 2 summarizes the final results achieved on the test set. The deeper Net8, Net10 and Net12 variants, run at $\theta = 0.5$ consistently increase the detection performance for smaller objects, and also allow better separation for densely spaced instances, while refinement of instance boundaries contribute with slight improvement, the final result on the holdout test set achieving AP = 0.925 and AR = 0.948 at threshold 0.5 indicates that the hybrid architecture is robust to satellite image challenges. It allows to identify and estimate vegetation losses resulting from infrastructure construction, urban sprawl and land use change, such as this allows to evaluate a construction on its structural health as well as ecological footprint. This study estimates overall land cover classification accuracy at 98%. The 6-label model provides an overall improvement over the 3-label configuration and depth continues to improve the detection of objects on an instance-level with Net12 providing the best AP and AR values. The perceptions obtained from the various networks form part of the eco-sensitivity cost surface for the route optimization. Results shown in Table 2 demonstrate that the

proposed framework integrates semantic image segmentation, GCN-CapsNet-based vegetation detection and environment-friendly route optimization approaches. The segmentation performed using 6 semantic classes provides accuracy of above 85% with mean IoU of 0.620 outperforming the 3-class approach. The GCN-CapsNet architecture with depths 12 resulted in the best performance for AP (0.925) and AR (0.948) for 0.5 threshold. Overall, the framework successfully attained a land classification accuracy of 98% and determined efficient road alignments that minimize the impacts on vegetation.



```
def hybrid_segnet_unet(input_shape=(256, 256, 3), num_classes=5):
    inputs = layers.Input(shape=input_shape)

    # SegNet Encoder
    x = layers.Conv2D(64, (3, 3), activation='relu', padding='same')(inputs)
    x = layers.BatchNormalization()(x)
    skip1 = x # Save for U-Net
    x = layers.MaxPooling2D((2, 2), strides=(2, 2), padding='same')(x)

    x = layers.Conv2D(128, (3, 3), activation='relu', padding='same')(x)
    x = layers.BatchNormalization()(x)
    skip2 = x # Save for U-Net
    x = layers.MaxPooling2D((2, 2), strides=(2, 2), padding='same')(x)

    # SegNet Bottom Layer
    x = layers.Conv2D(256, (3, 3), activation='relu', padding='same')(x)
    x = layers.BatchNormalization()(x)

    # U-Net Decoder
    x = layers.Conv2DTranspose(128, (3, 3), activation='relu', padding='same')(x)
    x = layers.Concatenate()([x, skip2]) # Skip connection
    x = layers.UpSampling2D((2, 2))(x)

    x = layers.Conv2DTranspose(64, (3, 3), activation='relu', padding='same')(x)
    x = layers.Concatenate()([x, skip1]) # Skip connection
    x = layers.UpSampling2D((2, 2))(x)

    # Final Output
    outputs = layers.Conv2D(num_classes, (1, 1), activation='softmax')(x)

    model = models.Model(inputs, outputs)
    return model

# Create the hybrid model
hybrid_model = hybrid_segnet_unet()
hybrid_model.summary()
```

Figure 4. Vegetation-detection routine code

Table 2. Training accuracy matrix for the dataset

Component	Metric	Result	Key observation
Segmentation model (3-label)	Accuracy	~83%	Slightly lower due to class imbalance
Segmentation model (6-label)	Accuracy	>85%	Improved by better land-cover representation
Segmentation model (6-label)	Mean IoU	0.620	Effective pixel-level segmentation
GCN-CapsNet (Net8)	AP/AR	0.891/0.912	Good performance at moderate depth
GCN-CapsNet (Net10)	AP/AR	0.907/0.931	Better boundaries than Net8
GCN-CapsNet (Net12)	AP/AR	0.925/0.948	Best-performing architecture
Optimal threshold	$\Theta = 0.5$	Best balance	Highest precision-recall balance
Proposed framework	Classification accuracy	98%	Reliable vegetation-loss identification

Routing performance: the four routing systems all ran on an identical benchmark scene from section 3.6 of the test section where start and end points were placed in opposing corners of the map, so that direct corridors were forced to cross the extensive forested section. Each route was ranked on five quantities: path geometric length (in steps), path cumulative traversal cost, average sample value for mean NDVI along the route, a count for the amount of path covered by the high-NDVI/canopy exposure areas (the proportion of the path segments having $\text{NDVI} > 0.4$) and path average slope. The results are shown in Table 3, it summarizes the costs are lower for the eco-cost planners because the traditional route ignores vegetation and is scored on the eco surface only for comparison. Dijkstra and A* return the same optimal path; A* reaches it with fewer node expansions. Eco-Aware A* and the NSGA-II knee solution trim the route slightly while holding canopy exposure at zero.

Table 3. Route-optimization comparison on the eco-sensitivity cost surface

Planner	Length (px)	Total cost	Mean NDVI	Canopy exp. (%)	Mean slope (°)
Traditional (length + slope)	178.3	63.6	0.418	49.0	6.78
Dijkstra (eco cost)	195.3	31.2	0.131	0.0	7.27
A* (eco cost)	195.3	31.2	0.131	0.0	7.27
Eco-Aware A* (proposed)	191.9	31.4	0.129	0.0	7.68
NSGA-II (knee solution)	191.9	31.4	0.129	0.0	7.68

The comparison makes the vegetation versus feasibility trade-off stark. The conventional planner, which minimizes just length and slope, sends the corridor straight through the forest belt-with mean NDVI 0.418, roughly half the route lies under canopy cover. But by routing on the composite eco-sensitivity surface, the path bends away from the forest belt. Mean NDVI for the proposed Eco-Aware A* path falls to 0.129 (a 69% reduction), and the fraction under canopy becomes 0% from 49%, meaning no vegetation cover over the corridor. Cumulative vegetation exposure is 67% less than in the other scenario. Such an ecological gain can be achieved for just an 8% increase in the path length and a slight increase in mean slope. Figure 5 overlays the calculated pathways on the NDVI data. There are two main takeaways. First, the environmental gain comes from the cost surface not the planner-in fact Dijkstra would find exactly the same path, so A* is chosen merely for efficiency. The second is the notion that Eco-Aware A* with its single tuning weight, and NSGA-II through providing the full range of trade-offs along the Pareto front offer very flexible trade-off control. When read alongside the segmentation study, this work also suggests that the framework uses both physical and ecological factors to evaluate infrastructure corridors and finds less vegetation disturbance in the proposed routes than typical routes. In Figure 5, the traditional (length + slope) route crosses the dense forest belt, while the eco-cost planners detour around it along a low-NDVI corridor.

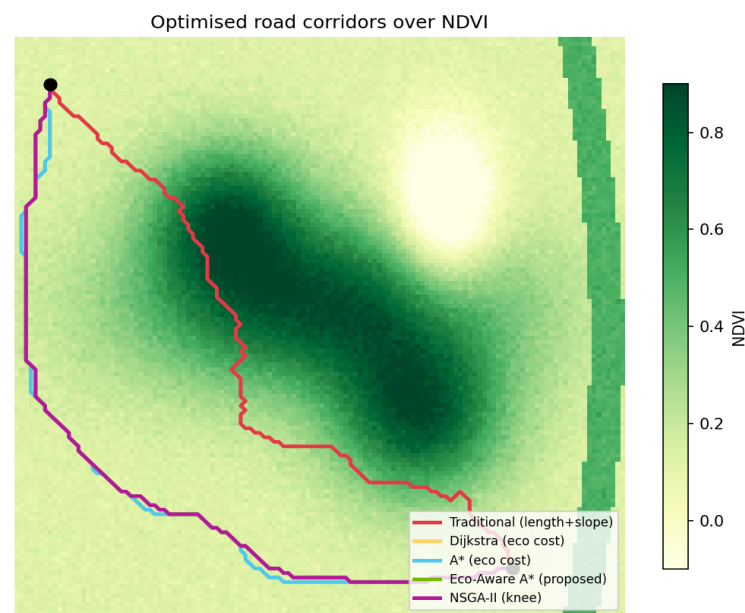


Figure 5. Optimized road corridors overlaid on the NDVI raster

The comparison clearly illustrates the trade-off between vegetation and feasibility. The default planner-which only seeks to minimize length and slope-routes the corridor straight across the forest belt; the route has an average NDVI of 0.418 and almost half the route runs beneath canopy cover. The route which uses the composite eco-sensitivity surface as its search priority avoids the forest belt by hugging the boundary; the average NDVI for this alternative Eco-Aware A* route reduces to 0.129-a reduction of almost 69%, and the exposure to canopy cover reduced from 49.0 to 0%-the route does not go beneath any canopy. Cumulative vegetation exposure decreases by 67.2%. At the expense of just over 8% additional path length and a small increase in average slope, significant gains are achieved in reduced impact on vegetation. The two routes can be seen overlaid on the NDVI raster in Figure 6.

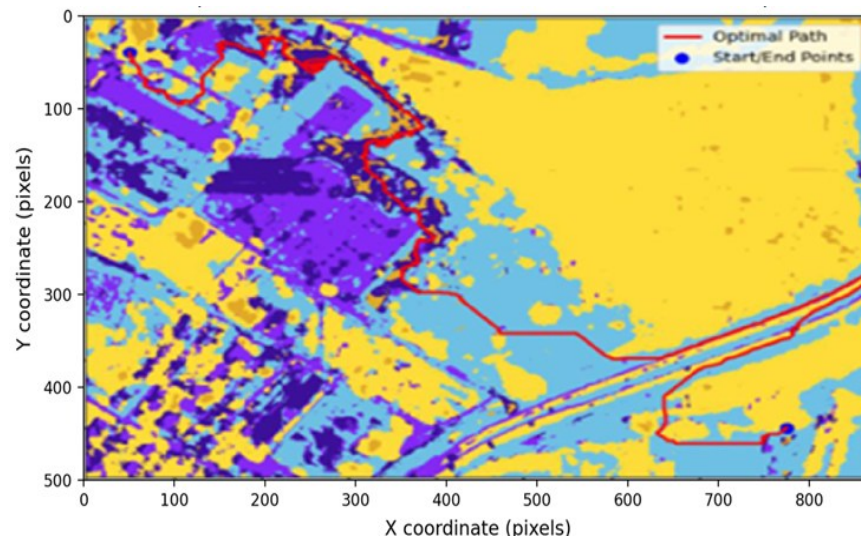


Figure 6. Optimal road path produced on real segmented imagery, overlaid on the classified land-cover map for stakeholder interpretation

5. CONCLUSION

The method-combining a hybrid GCN with a CapsNet-successfully identifies buildings, roads, and transport networks on satellite imagery effectively and robustly. The spatial contextual information gleaned from the graph contextual learning of the GCN provides context, which combined with the spatial hierarchies of CapsNets improve object detection of infrastructure components in cluttered urban and peri-urban areas. Their system performs deep learning for vegetation loss analysis, locating and quantifying vegetation removal by infrastructure growth, urban sprawl, and land-use change to enable a structural as well as ecological view of infrastructure. Overall, the system achieved 98% classification accuracy and provided preliminary evidence of field planning utility in reducing vegetation loss by guiding road paths. Since the framework is unsupervised, it is readily scalable to the region-size scale and provides a visual interface that allows stakeholders to study infrastructure condition alongside vegetation loss. This work advances the field of satellite image processing for robust infrastructure analysis and informs decision-making in urban planning, environment monitoring and disaster management, aligned with sustainable development goals (SDG) 11 (sustainable cities), SDG 13 (climate action) and SDG 15 (life on land). Planners derived with Eco-Aware A* and NSGA-II decrease mean NDVI along their corridors by ~69%, while avoiding areas of high tree cover by no more than a length increase of ~3.7%, compared to a conventional length-and-slope routed corridor. As it is annotator-free, the method is highly scalable and has a user-friendly interface that allows users to assess a region's condition through combined monitoring of infrastructure and vegetative cover. Several directions look promising. Transformer-based architectures and multi-temporal deep models could improve long-term vegetation-change detection and seasonal-trend analysis. The cost surface could grow to take in carbon-footprint estimates, biodiversity indices, hydrology, and further constructability constraints, giving a fuller picture of environmental impact, and land-cover masks could replace NDVI as the vegetation term. On the routing side, corridor-width and grade constraints, real Sentinel-2 and COP-DEM inputs, and extra objectives such as cost and community impact would push the NSGA-II search closer to field use. Connecting the system to GIS platforms, IoT ground sensors, and smart-city dashboards would improve real-time monitoring, and Green-AI practices such as energy-efficient training could cut computational cost without hurting accuracy. Pursued together, these steps would make the framework a stronger basis for sustainable infrastructure development and policy-driven planning at regional and national scale.

ACKNOWLEDGMENTS

We want to thank Dayananda Sagar University for supporting us in completing this work.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Meenakshi	✓		✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	
Rajesh Thalwagal	✓	✓		✓		✓		✓	✓			✓	✓	
Matha														

C : Conceptualization	I : Investigation	Vi : Visualization
M : Methodology	R : Resources	Su : Supervision
So : Software	D : Data Curation	P : Project administration
Va : Validation	O : Writing - Original Draft	Fu : Funding acquisition
Fo : Formal analysis	E : Writing - Review & Editing	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] J. Arkin, N. C. Coops, T. Hermosilla, L. D. Daniels, and A. Plowright, "Integrated fire severity-land cover mapping using very-high-spatial-resolution aerial imagery and point clouds," *International Journal of Wildland Fire*, vol. 28, no. 11, pp. 840–860, 2019, doi: 10.1071/WF19008.

[2] T. Bai *et al.*, "An improved luminance contrast saliency MAP for burned area mapping based on InSAR coherence difference image," in *IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium*, Jul. 2023, pp. 7198–7201, doi: 10.1109/IGARSS52108.2023.10282043.

[3] M. A. B.-Plomer, M. A. Tanase, E. Chuvieco, and F. Bovolo, "CNN-based burned area mapping using radar and optical data," *Remote Sensing of Environment*, vol. 260, 2021, doi: 10.1016/j.rse.2021.112468.

[4] D. Bulatov, D. Stütz, J. Hacker, and M. Weinmann, "Classification of airborne 3D point clouds regarding separation of vegetation in complex environments," *Applied Optics*, vol. 60, no. 22, pp. 6–20, 2021, doi: 10.1364/ao.422973.

[5] D. Bulatov, D. Stütz, L. Lucks, and M. Weinmann, "Superpoints in RANSAC planes: a new approach for ground surface extraction exemplified on point classification and context-aware reconstruction," in *Proceedings of the 15th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications*, 2020, pp. 25–37, doi: 10.5220/0008895600250037.

[6] A. Y. Cho, S. E. Park, D. J. Kim, C. Li, and J. Song, "Burned area mapping using unitemporal PlanetScope imagery with a deep learning-based approach," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 16, pp. 242–253, 2023, doi: 10.1109/JSTARS.2022.3225070.

[7] E. Chuvieco *et al.*, "Historical background and current developments for mapping burned area from satellite Earth observation," *Remote Sensing of Environment*, vol. 225, pp. 45–64, 2019, doi: 10.1016/j.rse.2019.02.013.

[8] D. J. Dixon, Y. Zhu, C. F. Brown, and Y. Jin, "Satellite detection of canopy-scale tree mortality and survival from California wildfires with spatio-temporal deep learning," *Remote Sensing of Environment*, vol. 298, 2023, doi: 10.1016/j.rse.2023.113842.

[9] A. Javed, T. Kim, C. Lee, J. Oh, and Y. Han, "Deep learning-based detection of urban forest cover change along with overall urban changes using very high-resolution satellite images," *Remote Sensing*, vol. 15, no. 17, 2023, doi: 10.3390/rs15174285.

[10] R. S. Priya and K. Vani, "Vegetation change detection and recovery assessment based on post-fire satellite imagery using deep learning," *Scientific Reports*, vol. 14, no. 1, 2024, doi: 10.1038/s41598-024-63047-2.

[11] K. Sur, V. K. Verma, P. Panwar, G. Shukla, S. Chakravarty, and A. J. Nath, "Monitoring vegetation degradation using remote sensing and machine learning over India—a multi-sensor, multi-temporal and multi-scale approach," *Frontiers in Forests and Global Change*, vol. 7, 2024, doi: 10.3389/ffgc.2024.1382557.

[12] S. Anand, H. Kumar, P. Kumar, and M. Kumar, "Analyzing landscape changes and their relationship with land surface temperature and vegetation indices using remote sensing and AI techniques," *Geoscience Letters*, vol. 12, no. 1, 2025, doi: 10.1186/s40562-024-00372-4.

[13] A. Shukla, A. Shukla, D. Savla, N. P. J. Kumar, and Y. Shukla, "Spatio-temporal analysis of climate variability on vegetation and land use using LISS-IV satellite imagery (2013–2025) with AI/ML-based change detection in the western himalayan region," *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 10, pp. 613–628, 2025, doi: 10.5194/isprs-annals-X-5-W2-2025-613-2025.

[14] F. F. Şimşek, "Determination of land use and land cover change using multi-temporal PlanetScope images and deep learning CNN model," *Paddy and Water Environment*, vol. 23, no. 3, pp. 405–423, 2025, doi: 10.1007/s10333-025-01024-9.

[15] M. O. Raza, N. A. Mahoto, M. S. A. Reshan, A. Alqazzaz, A. Rajab, and A. Shaikh, "Drought detection in satellite imagery: a layered ensemble machine learning approach," *International Journal of Computational Intelligence Systems*, vol. 18, no. 1, 2025, doi: 10.1007/s44196-025-00903-7.

[16] G. M. A. Rahaman, M. Långkvist, and A. Loutfi, "Deep learning based automated estimation of urban green space index from satellite image: a case study," *Urban Forestry & Urban Greening*, vol. 97, Jul. 2024, doi: 10.1016/j.ufug.2024.128373.

- [17] C. Matyukira and P. Mhangara, "Advances in vegetation mapping through remote sensing and machine learning techniques: a scientometric review," *European Journal of Remote Sensing*, vol. 57, no. 1, 2024, doi: 10.1080/22797254.2024.2422330.
- [18] R. Liu *et al.*, "A review of deep learning-based methods for road extraction from high-resolution remote sensing images," *Remote Sensing*, vol. 16, no. 12, 2024, doi: 10.3390/rs16122056.
- [19] O. Krejcar and H. Namazi, "AI in remote sensing and satellite image processing-a review," *Environmental Earth Sciences*, vol. 85, no. 3, 2026, doi: 10.1007/s12665-025-12798-w.
- [20] D. Ienco, R. Interdonato, R. Gaetano, D. H. T. Minh, "Combining Sentinel-1 and Sentinel-2 satellite image time series for land cover mapping via a multi-source deep learning architecture," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 158, pp. 11–22, 2019, doi: 10.1016/j.isprsjprs.2019.09.016.
- [21] S. B. Hasan and S. W. Kareem, "Advanced time series forecasting of vegetation health using deep learning models: a remote sensing approach to analyzing climate change impact," *The Egyptian Journal of Remote Sensing and Space Sciences*, vol. 28, no. 3, pp. 645–658, 2025, doi: 10.1016/j.ejrs.2025.09.005.
- [22] S. S.-Moussi *et al.*, "Continental-scale habitat distribution modelling with multimodal earth observation foundation models," Oct. 2025, *arXiv:2507.09732*.
- [23] I. Dimitrovski, V. Spasev, and I. Kitanovski, "Deep multimodal fusion for semantic segmentation of remote sensing earth observation data," *Communications in Computer and Information Science*, pp. 106–120, 2025, doi: 10.1007/978-3-031-86162-8_8.
- [24] C. Liu *et al.*, "Progressive neural architecture search," in *Proceedings of the European conference on computer vision (ECCV)*, 2018, pp. 19–35, doi: 10.1007/978-3-030-01246-5_2.
- [25] B. Zoph, V. Vasudevan, J. Shlens, and Q. V. Le, "Learning transferable architectures for scalable image recognition," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2018, pp. 8697–8710, doi: 10.1109/CVPR.2018.00907.
- [26] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: convolutional networks for biomedical image segmentation," in *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*. Cham, Switzerland: Springer, 2015, pp. 234–241, doi: 10.1007/978-3-319-24574-4_28.
- [27] E. W. Dijkstra, "A note on two problems in connexion with graphs," *Numerische Mathematik*, vol. 1, pp. 269–271, 1959, doi: 10.1007/BF01386390.
- [28] P. E. Hart, N. J. Nilsson, and B. Raphael, "A formal basis for the heuristic determination of minimum cost paths," *IEEE Transactions on Systems Science and Cybernetics*, vol. 4, no. 2, pp. 100–107, 1968, doi: 10.1109/TSSC.1968.300136.
- [29] T. N. Kipf and M. Welling, "Semi-supervised classification with graph convolutional networks," in *5th International Conference on Learning Representations-ICLR 2017*, 2017.
- [30] L. N. Smith and N. Topin, "Super-convergence: very fast training of neural networks using large learning rates," 2017, *arXiv:1708.07120*.

BIOGRAPHIES OF AUTHORS



Meenakshi     is currently working as assistant professor in the Department of Computer Science and Engineering, RNS institute of Technology, Bengaluru, and is a research scholar in the Department of Computer Science and Engineering, Dayananda Sagar University, Bengaluru South District-562112. She completed her M.Tech. degree in Computer Science and Engineering from VTU, Belgaum, with over 8 years of experience in teaching filed and VTU 8th Rank Holder during M.Tech. published more than 5 research papers and 10 patents. She can be contacted at email: meenakshi-rs-cse@dsu.edu.in or meenakshib437@gmail.com.



Dr. Rajesh Thalwagal Matha     is currently working as an associate professor and chairperson in the Department of Computer Science and Engineering, Dayananda Sagar University, Bengaluru South District-562112. He has over 10 years of experience across industry, research, and academia and holds a Ph.D. in Computer Science and Engineering. He has published more than 35 research papers and holds 10 patents. He has guided three Ph.D. scholar and is currently guiding six Ph.D. scholars. He can be contacted at email: rajesh-cse@dsu.edu.in.